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# A DEEP LEARNING APPROACH FOR FORECASTING GLOBAL COMMODITIES PRICES

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## ABSTRACT

Forecasting future values of time-series data is a critical task in many disciplines including financial planning and decision-making. Researchers and practitioners in statistics apply traditional statistical methods (such as ARMA, ARIMA, ES, and GARCH) for a long time with varying.
accuracies. Deep learning provides more sophisticated and non-linear approximation that supersede traditional statistical methods in most cases. Deep learning methods require minimal features engineering compared to other methods; it adopts an end-to-end learning methodology. In addition, it can handle a huge amount of data and variables. Financial time series forecasting poses a challenge due to its high volatility and non-stationarity nature. This work presents a hybrid deep learning model based on recurrent neural network and Autoencoders techniques to forecast commodity materials' global prices. Results show better accuracy compared to traditional regression methods for short-term forecast horizons (1,2,3 and 7 days).

**Keywords:** Deep learning, Machine Learning, Time Series Forecasting, Computer Intelligence, Recurrent Neural Network, LSTM

## I. INTRODUCTION

Accurate forecasting of future values of a financial time series poses a challenge due to its lack of predictability, high volatility, and non-stationarity nature. However, new methods in deep learning, specifically Recurrent Neural Networks (RNN) present non-linear end-to-end learning capabilities. RNN proofed effective in modeling complex casual and correlation relation types, and hence utilizing these tools to building predictive models for forecasting tasks that outperform traditional statistical methods.

RNN is applied in different fields in engineering, science, healthcare, and the economy. Contrasting to other disciplines, economic and finance phenomena's generate rapid fluctuating and high volatile time-series data sets. The biggest challenge here is building an inference model based on these datasets and other correlated factors datasets and use it for accurate forecasting. Despite such challenges, a successful application of RNN has achieved higher scores in forecasting capabilities better than other traditional methods, as we will show in the "related work" section.

This paper aims to prove that Deep Learning (DL) algorithms are capable of modeling and forecasting multivariate time-series data in financial discipline, with a higher degree of accuracy and generalization by building a data-driven predictive model using recurrent deep learning architectures.

In this research, a hybrid model of a stacked autoencoder and RNN is used to build and train the predictive model. To enhance and speed up the architecting process, we implement a genetic algorithm (GA) component as a helper tool to test prototypes, shorten the feedback cycle and come up with the best combinations of model hyper-parameters. Experiments' results show the achievements of specified objectives.

As a case study, the global gold price is chosen since gold plays an important role in economic and financial trading. Many researchers claim that gold.

price is an important financial indicator. In addition, many other commodities' prices are correlated with gold [1]. Gold price per troy ounce shows a steady upward trend since early 2008, that's because of the increase of world demand, especially in China and India [2].

## II. PROBLEM STATEMENT

Financial time series datasets that are generated from non-deterministic social and human behavior-based processes expose high volatility characteristics [3]. This high degree of volatility turns it challenging to statistically model it into a learnable distribution. Applying traditional regression tools results in modest forecasting performance.

The need for more accurate and reliable forecasting methods is the main drive for this research.

## III. RELATED WORK

In this paper [4], The forecast ARIMA (5,1,5) model has a forecast error of roughly 3.46 percent for the next day's forecast. The results of a typical ARIMA statistical method pale in comparison to the deep learning models provided in this and other papers. One advantage of ARIMA over deep learning is that it produces findings without the need for large datasets.

In this paper [5], Traditional statistical models, such as GARCH-class models with a long memory and fat-tail distributions, are used to predict and forecast gold futures volatility, with the ARMA model serving as the conditional returns. The ARMA (1, 1) model gives the best conditional returns, according to the findings. For in-sampling forecasting, the EGARCH and FIEGARCH



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models outperformed the other linear and non-linear GARCH-class models.

In this paper [6], Based on historical data on gold prices, the authors examine three prediction models: back-propagation neural network (BPN) [7], Principal Component Regression (PCR) [8], and Multiple Regression (MR). They employ gold's technical index values as independent variables and its closing price as a dependent variable. In comparison to other traditional models, the results suggest that BPN has a greater predictive capacity (MAPE: 1.6). However, we believe that the targeted aim, the same-day closing price, is too short-term and somewhat superficial to be of any benefit to investors.

This paper [9] Historical data on gold prices, silver prices, crude oil prices, the Standard and Poor's 500 stock index (S & P 500) index, and the foreign exchange rate are used to anticipate future gold prices for four commodities. The Extreme Learning Machine (ELM) [10] is a high-learning-ability learning technique for single hidden layered Feedforward neural networks. In addition, this research analyses five models: Feedforward networks with no feedback, Feedforward backpropagation networks, Radial basis function, ELMAN networks, and the ELM learning model. The findings show that ELM learning outperforms many other methods. The proposed ELM approach is insufficiently sophisticated.

In this paper [11], A conventional artificial neural network [12], trained by a backpropagation algorithm and the hybrid forecasting model of artificial neural network and genetic algorithms are proposed. The artificial neural network's neurons are optimized using a genetic algorithm. From 1987 through 2016, the monthly gold price per troy ounce in US dollars was utilized as the time series data. A MAPE 6.3374 error rate is achieved with this method, which, as will be shown below, is a poor result compared to this study results that are based on RNNs architecture.

In this paper [13], an Artificial Neural Network study has been implemented to forecast the prediction of precious metals such as gold, silver, platinum, and palladium prices by using RapidMiner data mining software. Comparing results with this study shows the superiority of deep learning models over traditional ANNs.

## IV. Methodology

From a dataset perspective, we perform data analysis and make use of the autocorrelation function, in addition to correlation with external factors that are used as predictors for the variable in hand. From a model architecture perspective, we depend on the power of Autoencoders to extract latent variable that holds the most contribution to the prediction process. In addition, we use RNN (LSTMs [14] or GRUs [15]) to capture the temporal dependencies between data steps. From a prediction perspective, we adopt the direct forecasting strategy. Forecasting horizons are short terms in 1, 2, 3, and 7 days.

### *A.* Data Modeling

In the experiments, we made use of a dataset of daily gold and other commodities materials prices. All values are in US Dollars currency units per troy ounce. The data recorded since 1970th. The datasets are publicly available at the Quandl data repository [16]. Plotting of a dataset is depicted in figure 1.


Figure 1: Gold daily prices

As we can infer visually, no seasonality in data and trend is generally increasing in various slow and fast degrees.



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The study employs two strategies to model data; 1) utilize autocorrelation relationships with gold historical prices. 2) utilize other commodity material historical prices (silver, oil) as input features.

Gold prices dataset is a time-series and is non-stationary. Measuring its non-stationarity using the Augmented Dickey-Fuller test [17] gives a p-value of 0.485405 (p-value > 0.05: Fail to reject the null hypothesis (H0), the data has a unit root and is non-stationary).

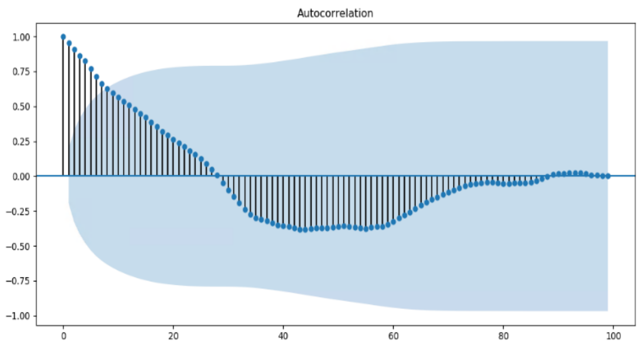


Figure 2: Autocorrelation function of daily gold prices

The autocorrelation function analysis shows a decreasing correlation with $x_{t-n}$ lags (autocorrelation decrease with lag-1, lag-2, lag-3, etc. respectively), check figure 2.

The heat map shown in figure 3 indicates which other commodity materials show the most correlation with gold. The data model is created in three steps:

1. using the ACF (autocorrelation function) to identify which auto-correlated lag values are most suitable for accurate prediction [18].
2. Factor correlation connections analysis and quantification for identifying external elements that are correlated to gold prices movements.
3. Selecting (manually or by GA module) The most important features that contribute to the gold prices predictability.

The biggest reliance on preceding lags is revealed by autocorrelation analysis and visualization (figure 2). It also exhibits gradual decreases in rows (lag-1, lag-2, lag-3, and lag-7) over time. To put it another way, the current day's pricing is linked to the prior days. The sort of correlation link, whether causal or association, requires an economic explanation, which is beyond the scope of this study because we are interested in forecasting rather than explaining the data [18]. Furthermore, developing an explanative model of the dataset is not a requirement. A closer examination of metals price time series reveals a strong association between gold and silver, as well as iridium and gas prices. Figure 3 depicts the correlation matrix.

We decided to build a predictive model based on lags (in gold; by days) and multivariate input of related commodities in this experiment (silver, iridium, and gas). We tried with various lag values (1, 2, 3, 7). Forecasts for the next day, two days, three days, and seven days.

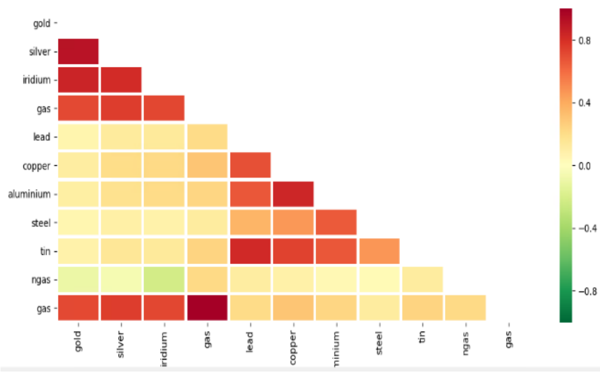


Figure 3: Correlation function between metals commodity materials

*B.* Model Architecture

What we are addressing in this study is to build a predictive model of data that forecasts future values in the short-term horizon. The study cast the problem as regression.

The input/output is sequences-to-sequence. Where we do many-to-one mapping, i.e., multi timesteps used to predict the next value. The features vector consists of several lags and external factors. The training strategy is normalizing the data in the range [0, 1], constructing features, split the dataset into training and testing parts. We utilize a hybrid model of deep learning methods; the model consists of two components; recurrent Variational autoencoder unit and LSTM units. TensorFlow [19] was used to create the model (An open-source machine learning framework developed by Google)

1) Recurrent Variational Autoencoder Component (RVAE)

Autoencoder component plays the role of learning representation of input features. It is

considered the second level of features selection. It accepts a vector of initially selected features, encode the input into a higher-level representation that gives varying weights to the latent variable that most affect the overall learning process, and outputs a new feature that provides a high degree of correlation with a target variable [20].

$$\boldsymbol{p}(\boldsymbol{x}, \boldsymbol{z}) = \boldsymbol{p}(\boldsymbol{x} \mid \boldsymbol{z})\boldsymbol{p}(\boldsymbol{z}) \quad (1)$$

RVAE explicitly map the dependencies between latent variable over subsequent timesteps, in addition to preserving the ability to model non-linear dynamics of the data.

2) LSTM Component

LSTM layers record the temporal structure between the lag and the target value after the RVAE component. It keeps track of the system's memory state. The depth necessary to describe high nonlinearity dynamics is provided by stacking LSTMs in multilayers.

3) Genetic Algorithm (GA) Component

The GA component implements a guided search to come up with better parameter values. The idea behind using GA is that finding the most stable and accurate model requires many trials and involves many parameters and component combinations. Significant time and headaches will be saved if such a task is recast as an approximate searching problem. This technique promotes and accelerates the architectural process.

GA searches for the following parameters categories:

- ANN Model hyper-parameters; Number of layers, Number of units per layer, Dropout rate and Learning rate.
- Training parameters; optimizer type, number of epochs, loss function, RNN type (LSTM, GRU) and batch size.
- features modeling parameters; timesteps and input features.

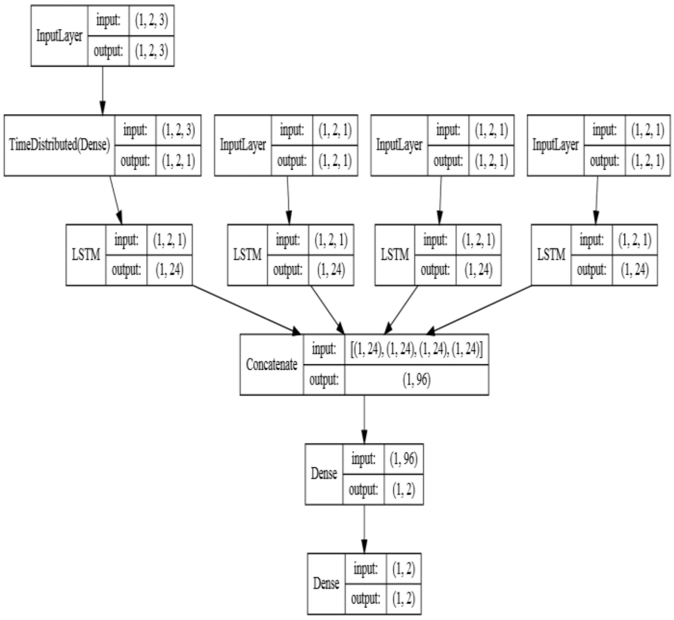


Figure 4: Model Architecture

## V. Experiments and Results

### A. Experiments Setup

These research experiments are implemented on 2.6 32-core Xeon processors and 64GB RAM. The machine learning framework chosen is Keras on top of the open-source Google TensorFlow [19]. The programming language is python 3.6. The used baseline system is GMDH Shell 3 with an education license [22].

The analysis of experimental results reveals that our strategy succeeds in addressing both aforementioned problems, accumulated feedback error multi-step recursive prediction and the lack of capturing the dependencies in multi-step direct prediction. with minor pitfall regarding dropped



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accuracy in certain points, such pitfall later is addressed in future research.

1) Performance Results

In this study, we utilize three metrics to evaluate the test result forecast of the model: MAE, RMSE and MAPE. MAE (Mean Absolute Error) is scale-dependent on the scale of the data [21] and is the average vertical distance between predicted and ground truth values. MAE computed by the following:

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (2)$$

RMSE (Root Mean-Square Error) is also scale-dependent on the scale of the data, however more sensitive to outliers.

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \quad (3)$$

MAPE (Mean Absolute Percentage Error) is a measure based on percentage errors and have the advantage of being scale-independent, and so frequently used to compare forecast performance across different datasets.

$$\mathbf{MAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - x_i}{y_i} \right| \quad (4)$$

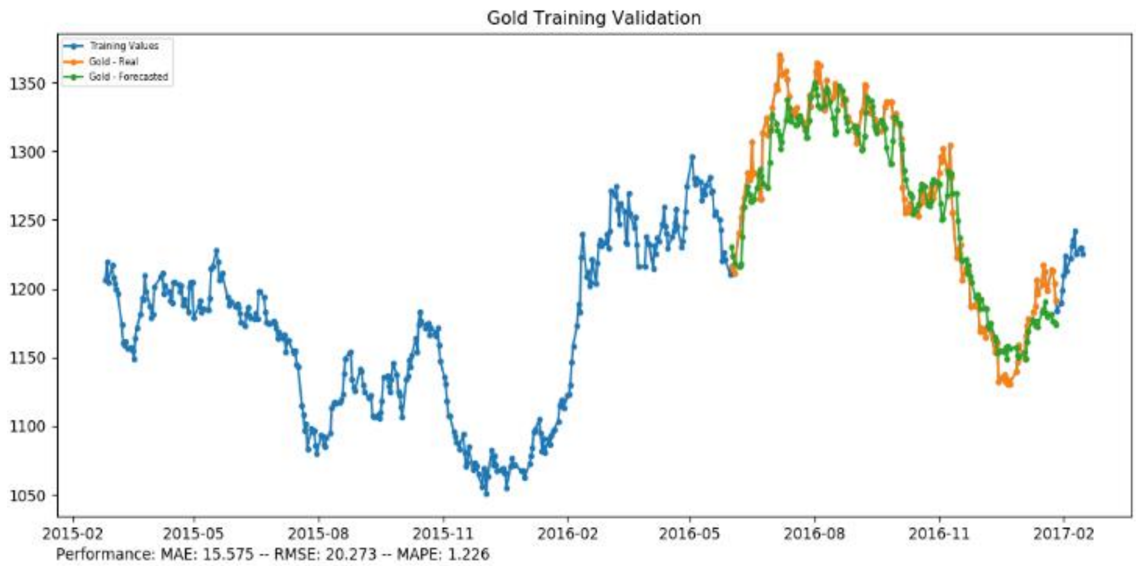


Figure 5: Forecasting Results

Table 1: Proposed model performance at different time lags

| Model | Lag-1 | Lag-2 | Lag-3 | Lag-7 |
|---|---|---|---|---|
| MAE | 15.7 | 15.57 | 23.31 | 38.54 |
| RMSE | 20.8 | 20.3 | 29.32 | 50.94 |
| MAPE | 1.15 | 1.23 | 1.89 | 3.16 |

Table 2: Proposed model performance (mape) compared to selected baseline model.

| Model | Proposed | GMDH |
|---|---|---|
| Lag-1 | 1.15 | 1.75 |
| Lag-2 | 1.23 | 2.12 |
| Lag-3 | 1.89 | 2.26 |
| Lag-7 | 3.16 | 3.96 |
| **Mean.** | **1.86** | **2.52** |

## VI. CONCLUSION

The results show that LSTM combined with a Genetic Algorithm and careful selection of features provides a powerful predictive model. The proposed model achieves a 1.15% prediction error (MAPE) for the next-day forecasting of gold materials. Which is superior to comparing similar work. In addition, day-2, day-3, and day-7 forecasting horizon results proved the stability of the model.

GA proved to be a powerful helper device for the model architect that succeeded in the selection of hyper-parameters, model parameters, and other properties. Future work will involve further elaboration on the model structure for more



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accurate forecasting and increased robustness of results. In addition to automating more functions of the model architecting process.

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